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ABSTRACT

Using the stochastic frontier analysis (SFA) model, we estimate total-factor energy efficiency (TFEE) scores for 47 regions across Japan during 1996–2008. We extend the cross-sectional SFA model proposed by Zhou et al. (2012) to panel data models and add environmental variables. The results provide not only the TFEE scores, in which statistical noise is taken into account, but also the determinants of inefficiency. The three SFA TFEEs are compared with a TFEE derived from data envelopment analysis (DEA). The four TFEEs are highly correlated with one another. For the inefficiency

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estimates, the higher the manufacturing industry share and wholesale and retail trade share, the lower the TFEE score.

Keywords: Stochastic frontier analysis (SFA), Data envelopment analysis (DEA), Total-factor energy efficiency (TFEE), Panel data, Shephard distance functions

1 Introduction

After the Fukushima Daiichi nuclear disaster on March 11, 2011, energy conservation has been an urgent issue in Japan. All 54 nuclear reactors in Japan were shut down immediately following the accident. The resulting shortages in electricity supply made “setstuden,” which means saving electricity in English, into a mantra throughout Japan. In July 2012, the Japanese government decided to reactivate Reactors #3 and #4 of the Oi nuclear power plant in response to the electricity shortages experienced in the Kansai Electric Power Company’s jurisdiction in summer 2012. Both reactors, however, were shut down again in September 2012 following a periodical check.

Although a new feed-in tariff to promote renewable energy was introduced in July 2012, it cannot fully make up for the shortfall resulting from the cessation of nuclear power generation. Despite the full capacity operation of the country’s thermal power plants - including some plants inactive before the Fukushima disaster due to outdated technology - and efforts by firms and households to save energy, serious electricity shortages remain. Vivoda (2012) asserted that nuclear reactors should be restarted as soon as possible because Japan is facing an energy security predicament. However, this is politically difficult given growing anti-nuclear public sentiment.

Severe energy constraints in Japan cause the following four serious problems.[1] First, dependence on fossil fuels for electricity generation amounted to 88% in 2012, which exceeds the 76% during the first oil crisis. Second, Japan loses approximately 3.6 trillion yen (3.5 million US dollars) per year in international trade related to importing additional fossil fuels after the Fukushima disaster - approximately 30 thousand yen (290 US dollars) per capita. Third, electricity prices are higher compared with those before the Fukushima disaster, with a standard family facing an average appreciation rate of 20%. Fourth, general electric utilities increased carbon dioxide emissions by 110 million tons, which corresponds to 9% of the nation's emissions in 2010. We believe that improving energy efficiency is one feasible solution to the above problems.

Energy is a fundamental factor from the viewpoint of both national

[1] See documents of the Follow-up Subpanel of Energy in the Industrial Competitiveness Council in Japan on December 20, 2013. (http://www.kantei.go.jp/jp/singi/keizaisaisei/bunka/energy/dai2/siryou.html)

security and the economy, and many empirical studies have examined energy efficiency. In this section, we classify these into three approaches.

The first is energy intensity, defined as energy consumption per unit of output, such as GDP or energy productivity (the reciprocal of energy intensity). This approach is considered the traditional energy efficiency index because it is easily calculated and has been widely used to compare countries (Nilsson, 1993; Miketa and Mulder, 2005; Mulder and De Groot, 2007; Le Pen and Sévi, 2010; Liddle, 2010). However, this approach combines energy with other inputs such as labor and capital stock. Therefore, energy intensity, as a partial-factor framework, is a limited approach in terms of measuring energy efficiency (Patterson, 1996; Hu and Wang, 2006).

The second approach is data envelopment analysis (DEA), a non-parametric linear programming methodology used to measure the efficiency of multiple decision-making units. Hu and Wang (2006) and Hu and Kao (2007) incorporated the total-factor energy efficiency (TFEE) index in the DEA model, resulting in an approach that was subsequently applied to Japan by Honma and Hu (2008, 2013), to Taiwan by Hu et al. (2012), and to OECD countries by Honma and Hu (2014). Moreover, Sözen and Alp (2009) compared Turkey's energy efficiency with that of the EU countries by incorporating energy consumption, greenhouse gas emissions, and local pollutants into the DEA model. Lozano and Gutiérreza (2008) proposed DEA models with undesirable outputs to estimate maximum GDP (minimum GHG emissions) compatible with given levels of population, energy intensity, and carbonization intensity (levels of population, GDP, energy intensity, or carbonization index). Mukherjee (2008) evaluated the energy efficiency of six sectors and found that the highest energy consumption occurs in the United States. Although DEA has been widely applied in energy efficiency studies, its drawback is that its efficiency analysissuffers from statistical noises.

The third approach is stochastic frontier analysis (SFA), which originated in Aigner et al. (1977) and Meeusen and van den Broeck (1977).[2] To overcome the statistical noise problem, several authors applied the SFA approach to measure energy efficiency. Filippini and Hunt (2011) measured economy-wide energy efficiency in OECD countries. Stern (2012) computed energy efficiency by applying SFA to 85 countries and examining the determinants of inefficiency. Herrala and Goel (2012) investigated global carbon dioxide

[2] For a comparison of DEA and SFA, see Hjalmarsson et al. (1996) and Iglesias et al. (2010).

(CO_2) efficiency (defined as the ratio of the CO_2 frontier to actual emissions) for more than 170 countries. Filippini and Hunt (2011) and Herrala and Goel (2012) employed a stochastic cost function, taking energy or CO_2 as the cost, in which GDP was a main explanatory output variable and neither labor nor capital stock data were used. On the other hand, Stern's (2012) model used labor and capital stock data, but energy intensity was an explanatory variable.

Unlike the above-mentioned studies, we measure energy efficiency on the basis of a standard Cobb–Douglas production function within the SFA approach. The study most closely related to ours is Zhou et al. (2012), who proposed a parametric frontier approach by using the Shephard energy distance function. Their approach essentially uses a single-output, production frontier model. One feature of their estimation technique is that it deems the reciprocal of energy consumption to be an output produced using labor, capital stock, and GDP as inputs. This methodology enables us to parametrically estimate energy efficiency, taking into account the statistical noise involved. Hu (2013) extends the cross-sectional model by Zhou et al. to a panel data model in order to measure the energy efficiency of regions in Taiwan.

The purpose of the present study is three-fold. The first is to extend the cross-sectional SFA model proposed by Zhou et al. (2012) to a panel data model and simultaneously estimate the determinants of inefficiency.[3] The second is to estimate the TFEE scores for 47 administrative regions in Japan during 1996–2008 and examine the effects of Japan's energy-saving policies over that period. The third is to compare the SFA results with those from DEA with respect not only to efficiency but also its determinants.

In our SFA model, efficiency measurements are based on the Shephard energy distance function, which is assumed to take the Cobb–Douglas functional form. Following Zhou et al. (2012), we also assume that the reciprocal of energy consumption is produced by GDP, labor, and capital stock. The maximum likelihood estimator is used to estimate the parameters, including the inefficiency component.

In a departure from the studies conducted by Zhou et al. (2012), Hu (2013), and Lin and Du (2013), we simultaneously estimate the determinants of inefficiency by employing the technical inefficiency effects model proposed by Battese and Coelli (1995). Before Battese and Coelli's study, a

[3] Recently, Lin and Du (2013), using the metafrontier procedure of Battese et al. (2004), also extended the model of Zhou et al. to conduct a panel data SFA estimation of the first stage of Chinese regional energy efficiency. However, their model does not include environmental variables (i.e., the model of Battese and Coelli, 1992).

two-stage approach was employed in which efficiency was estimated in the first stage; then, this estimated efficiency was regressed against the determinants in the second stage. Nowadays, this two-stage approach is severely criticized because both stages suffer from serious bias (Fried et al., 2008, p. 39).

On the other hand, the potential determinants of inefficiency can be estimated using the two-stage DEA model. However, this model presents two problems (Fried et al., 2008). One is the possible correlation between the input–output variables and the efficiency-determinant factors. The other arises from the fact that the interdependency of the DEA efficiency scores violates the basic assumption of independence within the sample. Instead of a non-parametric DEA approach, our parametric approach provides an alternative method to estimate efficiency and its underlying factors.

The rest of the study is organized as follows. Section 2 briefly review Japan's historical and current energy situation. Section 3 describes our methodology and data. Section 4 presents the TFEE results and the determinants of inefficiency for both SFA and DEA models. Section 5 discusses the results' implications. Section 6 concludes with a brief summary of the study.

2 Japan's Energy Situation

Prior to presenting the empirical methodology that this study employs, we briefly explain Japan's energy situation.

2.1 Historical review

Fig. 1 shows sector trends of final energy consumption since 1965. The industrial sector, and especially the manufacturing industry, emerges as the most energy consuming. Here, we divide energy consumption within the industrial sector into manufacturing and other industries.

Energy consumption in manufacturing drastically increased from 2.63×10^{18} J in 1965 to 6.43×10^{18} J in 1973, reflecting Japan's rapid economic growth. However, following the first oil crisis in 1973, one effect of which was the promotion of energy conservation across all sectors, energy consumption in manufacturing declined during the remainder of the 1970s. Since the 1980s, manufacturing has gradually increased its energy consumption, but in 2011, this declined to 5.80×10^{18} J in the wake of the economic slowdown triggered by the Lehman Brothers collapse.

In sum, although manufacturing production increased up to 1.6 times from 1973 to 2011, energy consumption shrunk 0.9 times in the same period. It should be noted that manufacturing comprises a substantial portion of nationwide energy consumption, but its energy productivity has improved following the first oil crisis by approximately 1.78 (=1.6/0.9) times. The curbing of energy consumption in manufacturing is mainly driven by progress in energy conservation and shifts in industrial structure (Ministry of Economy, Trade and Industry, 2013).

Final energy consumption in the commercial as well as industrial sectors increased until the first oil crisis, plateaued from 1973 to the early 1980s, and increased again after the late 1980s. This rise was caused by increases in gross floor area, air conditioning, and lighting equipment; development of office automation systems; and extension of business hours (Ministry of Economy, Trade and Industry, 2013).

Energy consumption in residential and transportation sectors also grew as a result of demand for convenience and amenities in housing and increases in private and freight vehicles, respectively.

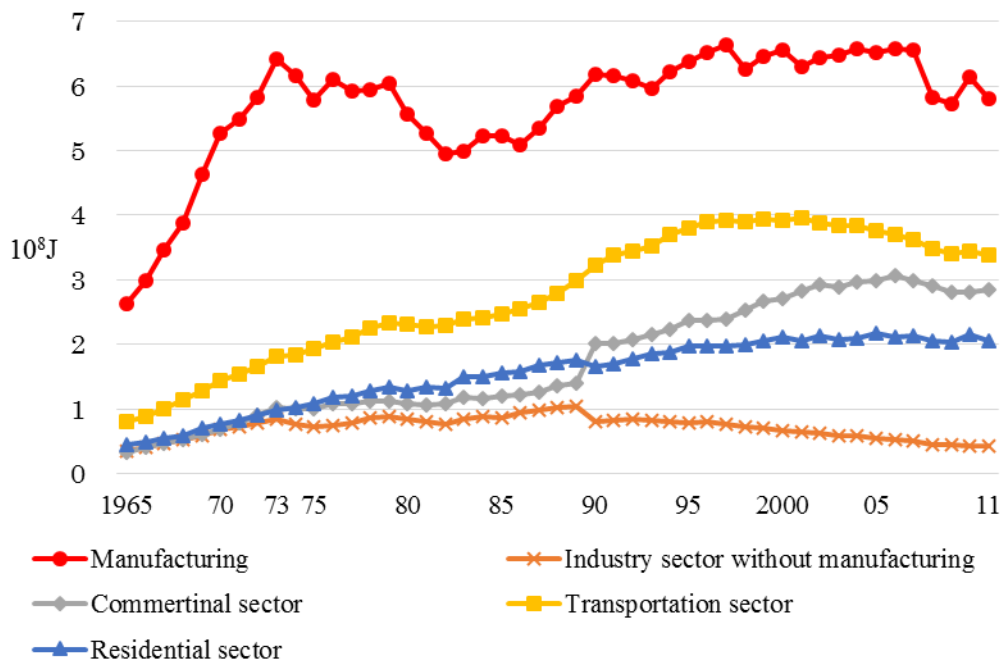
2.2 Japan's energy conservation policy

Historically, Japan has pursued an energy conservation policy since the first oil crisis in 1973. The Energy Conservation Law was enacted in 1979 and has since been revised eight times.

In this subsection, we explain the revisions to the law in our sample period, 1996–2008. The 1998 revision (effective April 1999) adopted the Top Runner Program, wherein a target standard value for a particular product (e.g., passenger vehicles, air conditioners, or TV sets) was established on the basis of the relevant product having the highest energy efficiency. Moreover, the Type 1 designated energy management category for factories consuming more than 3,000 kiloliters (kl) of crude oil equivalent per year with respect to fuel (heat) *or* electricity required the relevant factories to submit medium- and long-term energy conservation plans. In the 2002 revision (effective April 2003), the Type 1 designated energy management category was expanded from the five particular manufacturing industries to cover all industries. In addition, the Type 2 designated category of energy management required factories consuming more than 1,500 kl of crude oil equivalent per year to submit periodic reports. As a result of Japan's ratification of the Kyoto Protocol, the law was again revised in 2005 (effective April 2006). The Type 1 (Type 2) designated energy management category was expanded to include factories consuming more than 3,000 kl (1,500 kl) of fuel *and* electricity per year, and energy conservation measures for residential and construction sectors were strengthened.

As noted above, the Energy Conservation Law has been revised (strengthened) since the legislation was amended in response to the Kyoto Protocol.[4] We should thus examine whether such revisions exerted a significant effect on Japan's energy situation. Therefore, we require a more accurate measurement of regional energy efficiency.

[4] After the 2005 revision, the Energy Conservation Law was revised in 2008, 2011, and 2013. Although these subsequent revisions affect the country's energy situation, we do not refer to them because they occurred after the period of our study.



Note) In Japan's energy statistics, the calculation method changed in 1990.

Fig. 1. Trends of final energy consumption by sector. Source: Comprehensive Energy Statistics, 2013, Ministry of Economy, Trade and Industry, Japan.

2.3 After the Fukushima disaster

With regard to Japan's above-mentioned increasing energy demand, its energy supply is vulnerable. Because Japan is a resource-poor country, before the Fukushima disaster, the Japanese government promoted nuclear power generation in order to diversify energy sources. The Basic Energy Plan (2010) targeted the nuclear share in the country's power generation to be boosted from 24% in 2008 to by 50% in 2030. This strategy was abandoned by the aftermath of the Fukushima disaster, but no new strategy has been planned as of February 2014.

Owing to the absence of nuclear power generation after the Fukushima disaster, Japan faces a grave electricity shortage. The Japanese government repeatedly urged the public to save electricity. In the summer of FY2011, the Japanese government requested a 15% reduction in maximum electricity use during peak periods and times for all power users and issued Article 27 of Japan’s Electricity Business Act, “Restriction on Use of Electricity,” for large power users in areas under the Tokyo Electric Power Co., Inc. and Tohoku Electric Power Co., Inc. In the winter of FY2011, the Japanese government again requested households and firms to save electricity and set savings targets for the districts under the Kansai Electric Power Co., Inc. and Kyushu Electric Power Co., Inc. Furthermore, in the summer of FY2012, the government’s requests covering the saving targets in central, and western parts of Japan were relaxed following the restart of the Oi nuclear power plant. In the winter of FY2012, the saving target set for the district under the Hokkaido Electric Power Co., Inc., called for a 7% reduction in electricity use compared with that in FY2010.

The above measures had significant impacts not only on electricity consumption but also on economic activities. Morikawa (2012) surveyed more than 3,000 firms and determined that 45% of Japanese firms have been directly or indirectly affected by the rolling blackouts and regulation of electricity usage.

3 Methodology and Data

3.1 SFA model for input efficiency

Zhou et al. (2012) apply the single-equation, output-oriented SFA model to estimate the TFEE. Their cross-sectional SFA model was used to analyze 21 OECD countries in 2001. Combining the studies by Zhou et al. (2012) and Battese and Coelli (1992), this study extends the panel data SFA model further by estimating the TFEE.

Following Zhou et al., we assume that the stochastic frontier distance function is included in the Cobb–Douglas function as

$$\ln D\,(K_{it}, L_{it}, E_{it}, Y_{it}) = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln E_{it} + \beta_Y \ln \mathrm{Y}_{it} + v_{it}, \quad (1)$$

where $D(\cdot)$ is the distance function, K_{it} is the capital stock, L_{it} is labor employment, E_{it} is the energy input, Y_{it} is the real economic output, i indicates the region, t indicates the time, and v_{it} is the statistical noise following a normal distribution. Because the distance function is homogeneous to one degree in the energy input, the above equation can be rearranged as

$$\ln D_E (K_{it}, L_{it}, E_{it}, Y_{it}) = \ln E_{it} + \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln 1 + \beta_Y \ln \mathrm{Y}_{it} + v_{it}, \tag{2}$$

which can be also be arranged as

$$-\ln E_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln 1 + \beta_Y \ln \mathrm{Y}_{it} + v_{it} - \ln D_E (K_{it}, L_{it}, E_{it}, Y_{it}). \tag{3}$$

That is,

$$\ln(1/E_{it}) = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_Y \ln \mathrm{Y}_{it} + v_{it} - u_{it}, \tag{4}$$

where u_{it} is the inefficiency term, which follows a non-negative distribution, and $v_{it} - u_{it}$ is the error component term of a stochastic production frontier. Eq. (4) fits with the panel data stochastic frontier model proposed by Battese and Coelli (1992). The free software Frontier Version 4.1, kindly provided by Professor Coelli (1996), can be used to estimate Eq. (4). The TFEE of region i at time t is then

$$\mathrm{TFEE}_{it} = \exp(-u_{it}). \tag{5}$$

Therefore, we can apply the panel data stochastic production frontier approach to estimate the TFEE, but we are limited in the use of the input-oriented DEA suggested by Hu and Wang (2006) and Hu and Kao (2007). Moreover, if we use disaggregated energy inputs, we can also change the logged inverse energy inputs on the left-hand side of Eq. (4) and keep the other logged inputs on the right-hand side such that we can obtain the TFEE scores of different energy inputs.

Battese and Coelli (1995) further added an inefficiency equation for simultaneous estimations with the stochastic frontier in the form of Eq. (4):

$$u_{it} = \delta_0 + \delta_1 z_{it}^1 + \ldots + \delta_H z_{it}^H + \varepsilon_{it}, \tag{6}$$

where the $z^1, \ldots, z^H$ are environmental variables and ε is white noise following a normal distribution. As a result, we can simultaneously estimate Eqs. (4) and (6) by applying the approaches of Battese and Coelli (1995) and Coelli (1996).

3.2 DEA

DEA is a linear programming method used to assess the comparative efficiency of decision-making units (DMUs) such as countries, regions, firms, and other organizations. There are K inputs and M outputs for each of the N regions. Since the SFA model finds a frontier with curvature, we assume variable returns to scale (VRS) in the DEA model. The VRS envelopment of the i-th region can be derived using the following linear programming problem, proposed by Banker et al. (1984):

$$\text{Min}_{\theta, \lambda}\ \theta$$

$$\text{s.t.} -y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$e\lambda = 1$$

$$\lambda \geq 0, \qquad (7)$$

where θ is a scalar that represents the efficiency score of the i-th DMU, e is a 1 × N vector of ones, λ is an N × 1 vector of constants, y_i is an M × 1 output vector of DMU i, Y is an M × N output matrix composed of all output vectors of the N DMUs, x_i is a K × 1 input vector of DMU i, and X is a K × N input matrix composed of all input vectors of the N DMUs.

The efficiency score satisfies $0 \leq \theta \leq 1$, which is a radial contraction coefficient for the inputs. If $\theta = 1$, DMU i operates on the efficiency frontier and is technically efficient. This is an input-oriented model in which the radial adjustment coefficient, θ, multiplies the input vector of DMU i.

To control the annual environment, all efficiency scores and input targets for region i in year t are determined by comparing them to the regional efficiency frontier in year t. That is, the VRS-DEA model in this study uses regional observations in the same year.

In the second-stage regression, determinants of inefficiency are estimated by the following equation:

$$-\ln(\text{TFEE}_{it}) = \gamma_0 + \gamma_1 z_{it}^{1} + \ldots + \gamma_H z_{it}^{H} + \varepsilon_{it}, \qquad (8)$$

where ε is white noise following a normal distribution. Since $\text{TFEE}_{it}^{\text{SFA}} =$

$\exp(-u_{it})$ in the SFA model, for consistency, we take the corresponding inefficiency term in the DEA, $u_{it} = -\ln(\mathrm{TFEE}_{it}^{\mathrm{DEA}})$, as the dependent variable in the second-stage regression. Because the dependent variable $-\ln(\mathrm{TFEE}_{it}^{\mathrm{DEA}})$ is censored at zero when $\mathrm{TFEE}_{it} = 1$, we use the Tobit regression left censored at zero.

3.3 Data and variables

In our SFA model, we assume that the reciprocal of energy consumption is based on regional real GDP (million yen), labor (person), and capital stock (million yen). These data are taken from the Economic and Fiscal Model by Prefecture (Cabinet Office, Government of Japan), where all monetary values are given in million yen based on the year 2000 and labor is represented by the number of employees.

Data on energy are taken from the Energy Consumption Statistics by Prefecture (Agency for Natural Resources and Energy, Japan), where aggregated energy consumption is the sum of oil, gas, coal, electricity, and industrial heat presented in terms of thermal units (tera joules [TJ]). In contrast with previous studies that take regional/national energy consumption as a whole as one input (Hu and Wang, 2006; Hu and Kao, 2007; Honma and Hu, 2008; Hu et al., 2012; Zhou et al., 2012), our aggregated energy consumption data do not include residential and transportation sectors or non-energy use. Residential energy consumption, such as cooking, heating, and hot water supply system generate no value added and are hence excluded from the aggregated energy consumption data. For the same reason, energy consumption by private vehicles is also excluded. Energy consumption in the business transportation sector is unavailable because fuel consumed outside regional borders cannot be accurately allocated by region in the statistics. Using the selected energy consumption data allows more precise measurement of energy efficiency than was previously possible.

We employ industry shares as the environmental variables in two technical inefficiency effects models.[5] The first model (whose efficiency score is hereafter referred to as $TFEE^{SFA,M}$) includes as environmental variables the regional GDP shares of the manufacturing industry, service activities, and both wholesale and retail trade. The second model (hereafter $TFEE^{SFA,E}$) replaces

[5] Aside from industry shares, there are other candidates for environmental variables, such as social variables (e.g., population density) and natural variables (e.g., mean temperature and yearly precipitation). Because many of these variables are correlated with industry shares (e.g., the service industry is likely to be located in highly populated areas), we refrain from adding more environmental variables in order to avoid multicollinearity.

the manufacturing share with shares of five energy-intensive industries, namely, chemicals; iron and steel; non-ferrous metals; non-metallic mineral products; and pulp, paper, and paper products.

Data on industry shares are taken from the Annual Report on Prefectural Accounts (Cabinet Office, Government of Japan). The data on each energy-intensive industry's shares exclude Okinawa Prefecture because such data are unavailable for this prefecture, which comprises several small islands. All data are annual, and as mentioned earlier, the sample period spans 1996–2008. Table 1 summarizes the input, output, and environmental variable statistics.

Table 1

Statistical summary of inputs, outputs, and environmental variables

Variable	Unit	Mean	SD	Min	Max	Obs
Regional GDP	million yen	11,267,620	14,899,507	2,070,534	100,982,870	611
Labor	person	1,358,697	1,437,445	300,652	8,746,255	611
Capital stock	million yen	36,051,479	34,440,744	7,662,999	230,327,688	611
Energy	TJ	203,883	221,225	28,331	1,181,999	611
Manufacturing industry share	proportion	0.21239	0.07702	0.04031	0.43107	611
Chemical industry share	proportion	0.01798	0.01867	0.00021	0.10745	598
Iron and steel industry share	proportion	0.01395	0.01466	0.00044	0.10167	598
Non-ferrous metals industry share	proportion	0.01359	0.00945	0.00198	0.09322	598
Non-metallic mineral products industry share	proportion	0.00854	0.00588	0.00124	0.03798	598
Pulp, paper, and paper products industry share	proportion	0.00575	0.00591	0.00006	0.04200	598
Service activities share	proportion	0.19281	0.02771	0.11619	0.29261	611
Wholesale and retail trade industry share	proportion	0.11268	0.03134	0.05782	0.21673	611

4 Results

4.1 TFEE scores

The maximum likelihood estimates of the TFEE scores are given in Table 2, together with the DEA TFEE. The estimates of the SFA TFEEs are calculated using Frontier 4.1 provided by Coelli (1996).[6] Space limitations allow us to show only the mean TFEE scores and rankings of the four TFEEs for 1996–2008. The TFEEs of each region are stable during the sample period. Following Zhou et al. (2012) and Hu (2013), $TFEE^{SFA,O}$ represents the estimated TFEE scores without the environmental variables, while following Hu and Wang (2006), Hu and Kao (2007), and Honma and Hu (2008), $TFEE^{DEA}$ represents the DEA TFEE scores under VRS assumptions. $TFEE^{SFA,O}$ and $TFEE^{DEA}$ are mainly presented here as comparisons with $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$.

It should be emphasized that the rankings are similar; nevertheless, the TFEE scores differ between the four methods. The maximum value of the DEA TFEE scores reaches unity since they do not take into account statistical noise. Tokyo, Nara, and Tottori achieve unity scores for $TFEE^{DEA}$ throughout the sample period.

[6] For more detail, see Coelli et al. (2005).

Table 2

Mean TFEE scores and rankings by region in Japan (1996-2008)

Region	$TFEE^{SFA,O}$	$TFEE^{SFA,M}$	$TFEE^{SFA,E}$	$TFEE^{DEA}$
Hokkaido	0.406 (33)	0.641 (25)	0.607 (25)	0.488 (33)
Aomori	0.528 (29)	0.574 (30)	0.567 (30)	0.526 (31)
Iwate	0.770 (14)	0.845 (14)	0.838 (13)	0.727 (22)
Miyagi	0.584 (23)	0.674 (22)	0.676 (21)	0.626 (28)
Akita	0.877 (9)	0.888 (9)	0.886 (10)	0.867 (12)
Yamagata	0.971 (3)	0.966 (1)	0.967 (1)	0.884 (11)
Fukushima	0.689 (17)	0.802 (16)	0.793 (15)	0.799 (16)
Ibaraki	0.181 (43)	0.225 (43)	0.223 (42)	0.243 (43)
Tochigi	0.564 (24)	0.614 (26)	0.623 (24)	0.664 (26)
Gunma	0.663 (18)	0.750 (17)	0.754 (16)	0.704 (23)
Saitama	0.53 0(28)	0.727 (19)	0.731 (18)	0.577 (29)
Chiba	0.105 (47)	0.146 (45)	0.144 (44)	0.128 (47)
Tokyo	0.562 (25)	0.951 (3)	0.949 (3)	1.000 (1)
Kanagawa	0.233 (40)	0.345 (39)	0.344 (38)	0.311 (41)
Niigata	0.513 (30)	0.656 (24)	0.637 (23)	0.671 (25)
Toyama	0.530 (27)	0.533 (32)	0.532 (31)	0.809 (14)
Ishikawa	0.920 (8)	0.889 (8)	0.907 (8)	0.943 (9)
Fukui	0.785 (11)	0.747 (18)	0.745 (17)	0.959 (7)
Yamanashi	0.964 (6)	0.881 (12)	0.900 (9)	0.987 (5)
Nagano	0.777 (13)	0.914 (7)	0.914 (7)	0.780 (17)
Gifu	0.617 (22)	0.704 (20)	0.701 (20)	0.659 (27)
Shizuoka	0.434 (32)	0.585 (29)	0.58 (28)	0.501 (32)
Aichi	0.305 (38)	0.479 (34)	0.469 (33)	0.414 (36)
Mie	0.207 (42)	0.229 (42)	0.230 (41)	0.312 (40)
Shiga	0.543 (26)	0.514 (33)	0.527 (32)	0.953 (8)
Kyoto	0.734 (16)	0.814 (15)	0.835 (14)	0.778 (18)
Osaka	0.375 (34)	0.599 (28)	0.589 (27)	0.481 (34)
Hyogo	0.254 (39)	0.352 (38)	0.347 (37)	0.337 (39)
Nara	0.982 (2)	0.887 (10)	0.916 (6)	1.000 (1)
Wakayama	0.349 (35)	0.341 (40)	0.338 (39)	0.464 (35)
Tottori	0.800(10)	0.690 (21)	0.704 (19)	1.000 (1)

Shimane	0.987 (1)	0.924 (5)	0.920 (4)	0.990 (4)
Okayama	0.111 (46)	0.125 (46)	0.125 (45)	0.162 (46)
Hiroshima	0.219 (41)	0.269 (41)	0.268 (40)	0.290 (42)
Yamaguchi	0.137 (44)	0.148 (44)	0.146 (43)	0.211 (44)
Tokushima	0.634 (20)	0.571 (31)	0.578 (29)	0.802 (15)
Kagawa	0.477 (31)	0.447 (36)	0.456 (34)	0.536 (30)
Ehime	0.337 (36)	0.363 (37)	0.361 (36)	0.389 (37)
Kochi	0.632 (21)	0.602 (27)	0.598 (26)	0.748 (19)
Fukuoka	0.328 (37)	0.452 (35)	0.448 (35)	0.345 (38)
Saga	0.967 (5)	0.919 (6)	0.917 (5)	0.964 (6)
Nagasaki	0.935 (7)	0.958 (2)	0.961 (2)	0.830 (13)
Kumamoto	0.785 (12)	0.882 (11)	0.881 (11)	0.736 (21)
Oita	0.117 (45)	0.115 (47)	0.116 (46)	0.168 (45)
Miyazaki	0.660 (19)	0.665 (23)	0.669 (22)	0.682 (24)
Kagoshima	0.758 (15)	0.853 (13)	0.844 (12)	0.739 (20)
Okinawa	0.970 (4)	0.938 (4)	na	0.919 (10)
Mean	0.570	0.621	0.614	0.640
SD	0.270	0.257	0.258	0.265
Max	0.987	0.988	0.988	1.000
Min	0.104	0.104	0.105	0.107

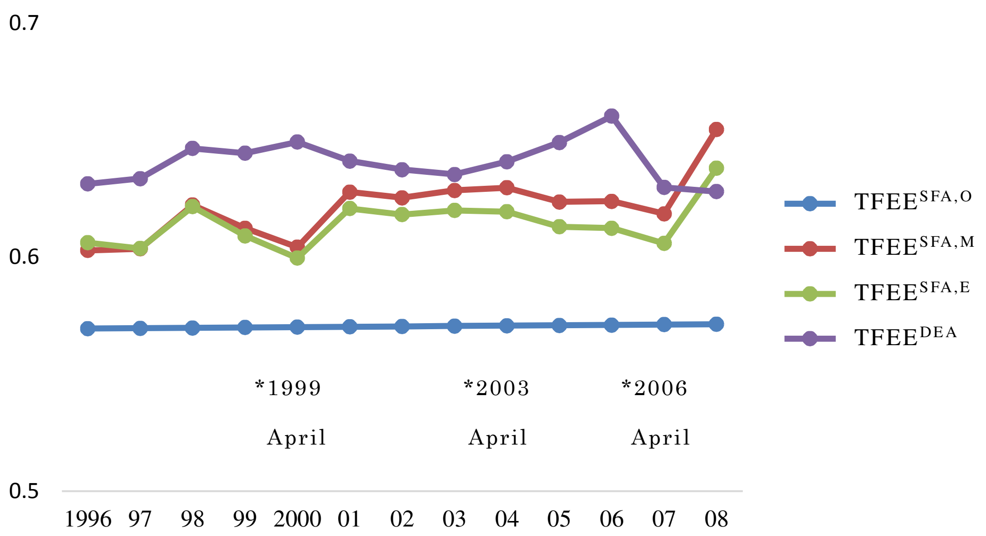
Note) Figures indicate the mean TFEE scores and parentheses indicate rakings in each column.

In comparing the four TFEEs, we observe that the rankings between TFEE^{SFA,M} and TFEE^{SFA,E} are similar, while those among others are not. There may be several explanations for why some regions experience different rankings between TFEE^{SFA,O} and TFEE^{SFA,M} and between TFEE^{SFA,O} and TFEE^{SFA,E}. Because the expected mean inefficiency terms in TFEE^{SFA,M} and TFEE^{SFA,E} vary across regions depending upon their individual environmental variables, regions located in a more advantageous environment are relatively more efficient. Tottori, Shiga, and Tokyo vary widely across the ranks of the TFEEs. Tottori is ranked first on $TFEE^{DEA}$ but 10th, 21st, and 19th on $TFEE^{SFA,O}$, $TFEE^{SFA,M}$, and $TFEE^{SFA,E}$, respectively. Shiga is ranked 8th on $TFEE^{DEA}$ but 33rd on $TFEE^{SFA,M}$ and 32nd on $TFEE^{SFA,E}$. Tokyo is ranked 1st on $TFEE^{DEA}$ but 25th on $TFEE^{SFA,O}$. This likely reflects whether statistical noise is considered. In addition, we assume that if a regional economy is far from average size, the estimated TFEE score is less accurate.

Next, we examine individual TFEE scores by region. The top three—Yamagata, Tokyo, and Nagasaki—show similar relationships between $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$. These regions have very high TFEE scores (exceeding 0.95), except for Tokyo's $TFEE^{SFA,E}$. This indicates that these regions have little room to save on energy consumption (less than 5%). Observing Tokyo's results, a significant divergence exists between the $TFEE^{SFA,O}$ and each of the $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ scores. This result may reflect Tokyo's more advantageous environment for the variables included in $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$. Chiba, Okayama, and Oita are the bottom three regions for all TFEEs and also show similar rankings between them.[7] Their

[7] Note that the number of regions except for $TFEE^{SFA,E}$ is 47, but except for $TFEE^{SFA,E}$ is 46.

TFEE scores for all four models are very low (<0.2), implying that energy saving has great potential (>80%) for all three regions.[8]



Note) Asterisks indicate when the various revisions of the Energy Conservation Law in Japan were enforced.

Fig. 2. Transition of mean TFEEs by model

Table 3

Pearson (below diagonal) and Spearman rank (above diagonal) correlation coefficients between the TFEEs by model

	$TFEE^{SFA,O}$	$TFEE^{SFA,M}$	$TFEE^{SFA,E}$	$TFEE^{DEA}$
$TFEE^{SFA,O}$	1	0.912	0.921	0.826
$TFEE^{SFA,M}$	0.931	1	0.998	0.761
$TFEE^{SFA,E}$	0.937	0.999	1	0.770
$TFEE^{DEA}$	0.843	0.808	0.814	1

The difference occurs because the TFEE scores cannot be calculated for Okinawa owing to a lack of data.

[8] We discuss improvement by regions that have very low TFEE scores in Section 5.1.

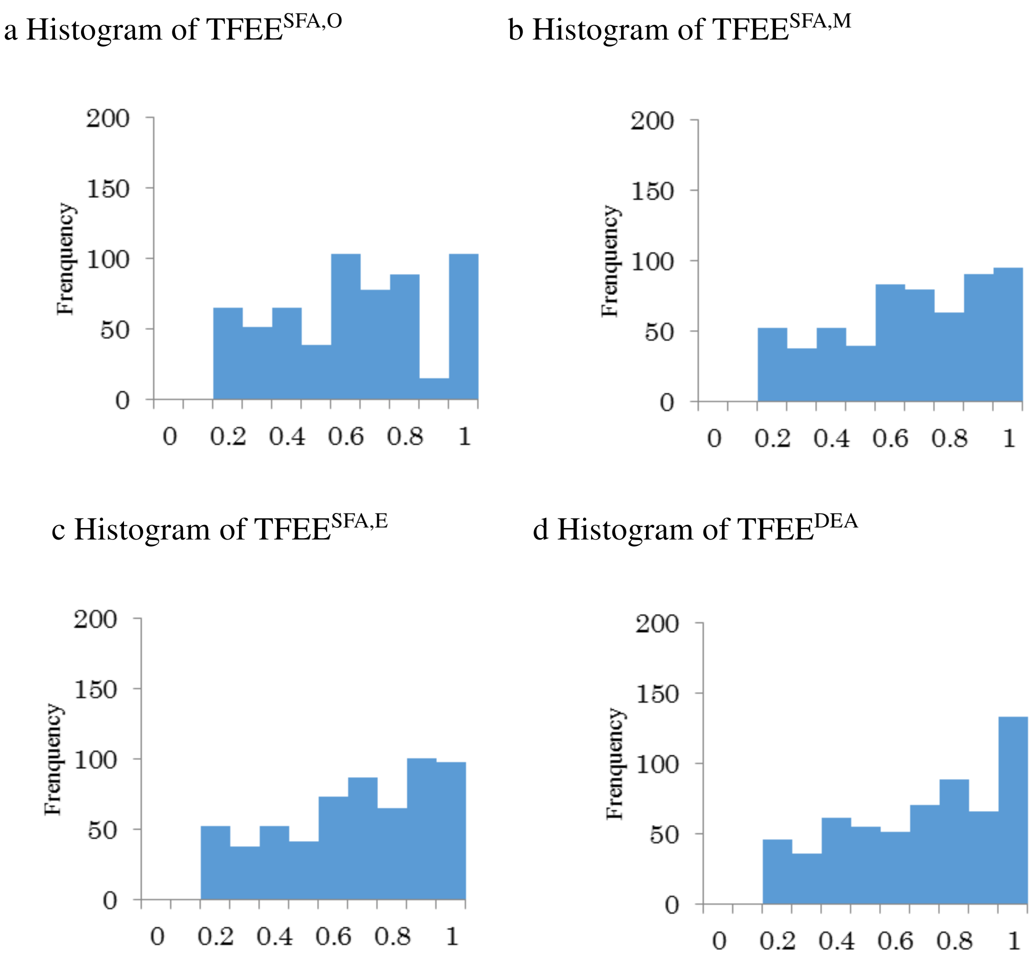


Fig. 3. Histograms of the TFEEs

Table 3 shows the correlation coefficients for the four TFEEs. Pearson correlation coefficients are presented below the diagonal and Spearman rank correlation coefficients are presented above the diagonal. The four TFEEs are highly correlated with one another. While the correlation coefficients between the three SFA TFEEs are larger than 0.9, those between the SFA TFEEs and DEA TFEE are around 0.8. All correlations in Table 3 are significant at the one percent level.

Figs. 3a–d present histograms of the four TFEEs during 1996−2008. In the histogram of $TFEE^{SFA,O}$, two peaks, 0.5-0.6 and 0.9-1.0, are observed, and the frequency drops in the 0.8-0.9 range (Fig. 3a). Only the histograms of $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ are very similar. In these histograms as well, two peaks are observed in the 0.6-0.7 and 0.8-0.9 ranges (Figs. 3b and c). In the histogram of $TFEE^{DEA}$, the peak is located in the 0.9-1.0 range (Fig. 3d).

Finally, we examine the trend of energy efficiency in the sample period. Fig. 2 presents the mean TFEE indexes by model. Each asterisk represents the timing of enforcement of the energy conservation laws in the sample period. The mean $TFEE^{SFA,O}$, $TFEE^{SFA,M}$, and $TFEE^{SFA,E}$ rise from 0.569, 0.603, and 0.606 in 1996 to 0.571, 0.654, and 0.638 in 2008, respectively. On the other hand, only mean $TFEE^{DEA}$ shows slight deterioration from 0.631 to 0.628. In sum, the above results suggest that energy efficiency in Japan improved during the period of study. This might partly be attributed to the revisions to the Energy Conservation Law.

4.2 Simultaneous estimates of determinants of inefficiency by SFA

Table 4 shows the estimated coefficients and determinants of inefficiency in the SFA TFEEs. Except for the coefficients of log regional GDP in $TFEE^{SFA,O}$ and $TFEE^{SFA,E}$, coefficients for the log regional GDP, log labor, and log capital stock are significant. However, these coefficients are not directly interpretable. For example, the coefficient of log GDP in $TFEE^{SFA,M}$ (0.306) means that a 1% increase in GDP reduces energy consumption by 0.306%. This finding is inconsistent with the standard production theory. We note that these implausible results may stem from the underlying assumption attributing inefficiencies regarding outputs and inputs to energy use.

In the ML estimates, variances of v and u, $\sigma_v{}^2$ and $\sigma_u{}^2$, are reparameterized as $\sigma^2 = \sigma_v{}^2 + \sigma_u{}^2$ and $\gamma = \sigma_u{}^2/\sigma^2$, respectively. The parameter γ must lie between 0 and 1 and indicates the relative contributions of u to the error components. The large values of γ (0.999, 0.999, and 0.994) for the three SFA TFEEs imply that the variance in the error components is almost explained by technical inefficiency.

The trend of the time-varying inefficiency parameter, η, (Battese and Coelli, 1992) is also estimated in $TFEE^{SFA,O}$ instead of the share variables. A positive (negative) η implies that efficiency decreases (increases) over time. For TFEE^{SFA,O}, η is slightly positive (0.001) but insignificant.

The determinants of inefficiency are simultaneously estimated for TFEE^{SFA,M} and TFEE^{SFA,E} using the technical inefficiency model (Battese and Coelli, 1995). Note that a positive (negative) coefficient of each industry's share implies an inefficiency reducing (inducing) factor. The estimated coefficients for the shares of manufacturing and wholesale and retail trade, 15.531 and 11.332, respectively, are highly significant, but that for the service industry is insignificant for TFEE^{SFA,M}. We find that the higher the shares of manufacturing and wholesale and retail trade, the lower the efficiency. The estimates of TFEE^{SFA,E} in Column 3 provide a more comprehensive analysis of the determinants of inefficiency. With the exception of the non-ferrous metals industry, which has a negative coefficient, the other four energy-intensive industries - chemical; iron and steel; non-metallic mineral products; and pulp, paper, and paper products - are highly significant in reducing efficiency. The wholesale and retail trade industry share continues to affect inefficiency levels, but its coefficient drops to a lower value in TFEE^{SFA,E} than in TFEE^{SFA,M}.

Table 4

Maximum likelihood estimates of the stochastic frontier function parameters for the Japanese regions

Variable	Inefficiency of $TFEE^{SFA,O}$	Inefficiency of $TFEE^{SFA,M}$	Inefficiency of $TFEE^{SFA,E}$
Constant (β_0)	−0.530	3.491***	2.912***
	(−0.458)	(6.940)	(6.804)
Log regional GDP	−0.069	0.306*	0.181
	(−1.271)	(1.861)	(1.451)
Log labor	−0.576***	−0.971***	−0.928***
	(−6.410)	(−7.492)	(−9.109)
Log capital stock	−0.084***	−0.354***	−0.239***
	(−2.827)	(−3.735)	(−2.907)
Constant (δ_0)		−5.369***	−1.640***
		(−2.389)	(−3.866)
Manufacturing industry share		15.531***	
		(4.187)	
Chemical industry share			18.872***
			(11.527)
Iron and steel industry share			35.694***
			(15.276)
Non-ferrous metals industry share			−8.696**
			(−2.517)
Non-metallic mineral products industry share			41.388***
			(7.098)
Pulp, paper, and paper products industry share			24.243***
			(4.925)
Service activities share		−4.120	−0.785
		(−0.610)	(−0.453)
Wholesale and retail trade industry share		11.332**	7.359***
		(2.504)	(6.392)
$\sigma^2 = \sigma_v{}^2 + \sigma_u{}^2$	2.311	1.397***	0.254***
	(0.986)	(3.982)	(9.846)
$\gamma = \sigma_u{}^2 / \sigma^2$	0.999***	0.999***	0.994***
	(1292.201)	(1646.483)	(353.468)
μ	−1.961		
	(−0.623)		
η	0.001		
	(0.956)		
Log likelihood	901.151	−287.998	−122.431
Number of observations	611	611	598
Number of regions	47	47	46

Note) *t*-values are in parentheses. Statistical significance at the one, five, and ten percent levels are indicated by ***, **, and *, respectively.

4.3 Second-stage estimates of the determinants of inefficiency by DEA

To compare with the simultaneous estimates of the determinants of inefficiency of $\mathrm{TFEE}^{\mathrm{SFA,M}}$ and $\mathrm{TFEE}^{\mathrm{SFA,E}}$, we regress the inefficiency of $\mathrm{TFEE}^{\mathrm{DEA}}$ on industry shares using the Tobit model. As in the previous subsection, we exclusively use the manufacturing industry share and the five energy-intensive industry shares.

Table 5 presents the results for the second-stage regression of the inefficiency of $\mathrm{TFEE}^{\mathrm{DEA}}$ on the environmental variables. Note that in the inefficiency equation of the SFA model, the inefficiency term is related to the efficiency score as $\mathrm{TFEE}_{it}^{\mathrm{SFA}} = \exp(-u_{it})$ for region i at time t. For consistency in the second-stage regression, the inefficiency term under DEA is obtained by the transformation as $u_{it} = -\ln(\mathrm{TFEE}_{it}^{\mathrm{DEA}})$ for region i at time t. Column 1 in Table 5 presents the estimation results involving the manufacturing industry share, which is significantly positive in Column 1. The higher the manufacturing industry share, the less efficient the energy use. Note that a coefficient of Tobit regression is generally not comparable with that of another model on account of the distortion to the distribution due to the censored data. However, in our model, the marginal effects computed are similar to the coefficients in Table 5. Related to the manufacturing share, the coefficients of $TFEE^{SFA,M}$, 15.531, in Table 4 are larger than corresponding coefficients for $TFEE^{DEA}$, 3.083, in Table 5. We hypothesize that this occurs mainly because the inefficiency terms in $TFEE^{SFA,M}$ depend upon the industry shares as the environmental variables in Eq. (6), whereas the efficiency measurement of $TFEE^{DEA}$ does not use industry shares. Signs for the shares of service activities and the wholesale and retail trade industry are positive, but it is significant so only for the latter.

Column 2 of Table 5 presents the estimation results involving the shares of the five energy-intensive industries. All coefficients of these industry shares are significant at the one percent level. Among them, energy-intensive industries, except the non-ferrous metals industry, are highly significant in reducing TFEE. Only the coefficient of the non-ferrous metals industry share is positive. These results are consistent with those for $TFEE^{SFA,E}$. Each (absolute) value of the coefficients for $TFEE^{DEA}$ is smaller than that of the corresponding coefficients for $TFEE^{SFA,E}$ in Table 4. This can be attributed to the same reason as that given above.

Table 5

Second-stage estimates of the determinants of inefficiency

Variable	Inefficiency of $TFEE^{DEA}$	
Constant	−0.872***	−0.536***
	(−2.746)	(−2.808)
Manufacturing industry share	3.083***	
	(7.478)	
Chemical industry share		10.571***
		(10.284)
Iron and steel industry share		22.117***
		(8.398)
Non-ferrous metals industry share		−10.245***
		(−8.142)
Non-metallic mineral products industry share		13.114***
		(3.432)
Pulp, paper, and paper products industry share		7.453***
		(2.831)
Service activities share	1.251	−0.014
	(1.105)	(−0.017)
Wholesale and retail trade industry share	4.514***	5.092***
	(6.402)	(8.712)
Sigma	0.556***	0.4203***
	(26.417)	(22.440)
Number of observations	611	598
Number of regions	47	46
Log likelihood	−520.207	−359.426

Note) Robust *t*-values are in parentheses. The statistical significance at the one, five, and ten percent levels are indicated by ***, **, and *, respectively.

5. Discussion

5.1 Policy implications of the TFEE scores

How should policy makers consider values of the various TFEE scores? In what follows, we discuss the policy implication of our TFEE results. It is ideal but implausible that all regions achieve scores near unity. As previously stated, inefficiency is successfully explained by industry shares, which cannot be radically changed. In addition, regions that specialize in energy-intensive industries supply energy-intensive goods to regions that barely produce them. In fact, industry composition should be taken as given to some extent.

Policy makers in an inefficient region may target a minimum efficiency level that could be achieved given the region's industry composition. This target can be set by comparing the regions that have similar industry compositions.[9] For example, Oita, which ranks at or near the bottom (0.115 in average $TFEE^{SFA,M}$), is located in a rural area but has higher shares of manufacturing and energy-intensive industries. Oita may target other rural regions with similar industrial compositions that nevertheless attain better TFEE scores, e.g., Yamaguchi (0.148 in average $TFEE^{SFA,M}$) and Okayama

[9] As for DEA, Olesen and Petersen (2009) proposed a target efficiency DEA model that includes environmental variables in a one-stage model.

(0.125), even if these scores are only slight improvements.

Although DEA suffers from statistical noise such as measurement errors, SFA does not. However, SFA needs to assume a functional form. To check robustness, policy makers should simultaneously examine both SFA and DEA efficiency indexes.

Finally, it should be pointed out that TFEE indicates relative efficiency, which is derived from comparisons in each year. Thus, technological innovation is crucial to improving absolute efficiency, but that topic is beyond the scope of this study.

5.2 Simultaneous estimation versus second-step estimation

One-step estimation by SFA is seemingly more desirable than two-step estimation by DEA because both efficiency and its determinants are simultaneously derived and because the effects of environmental variables are appropriately incorporated into its efficiency values. However, once we focus on the individual effect in the conventional panel data econometric model and take into account any unobserved heterogeneity of regions, we are left with a cumbersome problem, namely, that cross-regional heterogeneity and inefficiency should be differentiated. Related to $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$ on the basis of Battese and Coelli (1995), cross-regional heterogeneity is considered by varying the mean value of the inefficiency error term depending upon environmental variables. Note that in these efficiency formulations, any unobserved time-invariant cross-regional heterogeneity is considered as inefficiency.

However, in Eq. (3) of the stochastic approach, all regions have the same interception, β_0. This value can vary by region if unobserved heterogeneity exists. Greene (2005a, b) proposes the true fixed-effects model and true random-effects model to estimate unit-specific constants. This line of research should be explored in energy efficiency research. However, unobserved heterogeneity in the parameter estimates is beyond the scope of this study, in which our plain panel results serve as the benchmark.

Note that treatments of environmental variables differ between SFA and DEA (Schmidt, 2011). In SFA, we must use the environmental variables to separate noise and inefficiency; nevertheless, they do not affect the stochastic frontiers. On the other hand, in DEA, we can construct frontiers without using environmental variables. These two approaches differ significantly with regard to both efficiency measurement and estimates of the determinants of inefficiency. However, as shown in the previous section, the empirical results are similar. The SFA and DEA approaches are complementary and both should be employed as a robustness check.

6. Concluding remarks

This study parametrically and non-parametrically estimates the TFEE scores for 47 regions in Japan and the determinants of inefficiency for 1996–2008. We extend the SFA approach employed by Zhou et al. (2012) and Hu (2013) and incorporate the technical inefficiency effects model proposed by Battese and Coelli (1995). Our two technical inefficiency effects models exclusively include the manufacturing industry share and the five energy-intensive industry shares as environmental variables that influence inefficiency, the scores of which are referred to as $TFEE^{SFA,M}$ and $TFEE^{SFA,E}$, respectively. For comparison, a stochastic TFEE without environmental variables, $TFEE^{SFA,O}$, is also computed. In addition, we use the DEA technique to measure non-parametric TFEE under VRS, $TFEE^{DEA}$.

The four TFEEs are highly correlated with one another, especially $TFEE^{SFA,O}$, $TFEE^{SFA,M}$, and $TFEE^{SFA,E}$. The trend of the mean TFEEs suggests that energy efficiency improved during the sample period. However, there is considerable potential for further savings on energy consumption in the Japanese regions. For the bottom three regions—Chiba, Okayama, and Oita—the TFEE scores in all four models are very low (<0.2). This suggests the possibility of conserving more than 80% of energy in all three regions.

We compare not only the TFEEs but also the determinants of inefficiency between SFA and DEA. In SFA, the determinants are estimated simultaneously with inefficiency. This simultaneous estimation suitably incorporates influences from environmental variables into inefficiency. This is SFA's advantage over the two-step estimation in DEA. But in the SFA estimation, we must introduce additional assumptions regarding a functional form of the frontier and a distribution of inefficiency and error terms compared to DEA. On the other hand, the inefficiency of the DEA TFEEs is regressed on environmental factors via a Tobit approach. The signs of the Tobit model are consistent with those of the SFA estimation. For both SFA and DEA, the results that include the manufacturing industry share show that the higher the manufacturing and wholesale and retail trade shares, the lower the energy efficiency. The results that include energy-intensive industry's shares show that the higher shares of chemicals; iron and steel; non-metallic mineral products; and pulp, paper, and paper products industries, the significantly lower the levels of efficiency.

Our study has two limitations. First, in our SFA model, all inefficiencies are attributed to energy input. This may lead to overestimating energy inefficiency. On this point, DEA is superior to SFA because the DEA TFEE takes into account both radial and non-radial slack with respect to energy inputs. The second limitation is that the estimates do not consider unobserved heterogeneity.

Our approach can be extended in various directions. First, the environmental variables that affect energy efficiency should be further explored. It is important not only to measure efficiency but also to examine the determinants of inefficiency. Second, the functional form can be easily changed from the Cobb-Douglas function to more general functional forms such as a translog function. Third, undesirable outputs should be added to the stochastic models because energy consumption inevitably generates pollution in the form of emissions and waste.

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